PROBABILITY OF DEFAULT RATING METHODOLOGY REVIEW

by

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ABSTRACT

Institutions of the Farm Credit System (FCS) focus on risk-based lending in accordance with regulatory direction. The rating of risk also assists retail staff in loan approval, risk-based pricing, and allowance decisions. FCS institutions have developed models to analyze financial and related customer information in determining qualitative and quantitative risk measures. The objective of this thesis is to examine empirical account data from 2006-2012 to review the probability of default (PD) rating methodology within the overall risk rating system implemented by a Farm Credit System association. This analysis provides insight into the effectiveness of this methodology in predicting the migration of accounts across the association's currently-established PD ratings where negative migration may be an apparent precursor to actual loan default.

The analysis indicates that average PD ratings hold relatively consistent over the years, though the distribution of the majority of PD ratings shifted to higher quality by two rating categories over the time period. Various regressions run in the analysis indicate that the debt to asset ratio is most consistently statistically significant in estimating future PD ratings. The current ratio appears to be superior to working capital to gross profit as a liquidity measure in predicting PD rating migration. Funded debt to EBITDA is more effective in predicting PD rating movement as a measure of earnings to debt than gross profit to total liabilities, although the change of these ratios over time appear to be weaker indicators of the change in PD rating potentially due to the variable nature of annual earnings of production agriculture operations due to commodity price volatility. The debt coverage ratio is important as it relates to future PD migration,

though the same variability in commodity price volatility suggests the need implement multi-year averaging for calculation of earnings-based ratios. These ratios were important in predicting the PD rating of observations one year into the future for production agriculture operations.

To further test the predictive ability of the PD ratings, similar regression analyses were completed comparing current year rating and ratios to future PD ratings beyond one year, specifically for three and five years. Results from these regression models indicate that current year PD rating and ratios are less effective in predicting future PD ratings beyond one year. Furthermore, because of the variation in regression results between the analyses completed for one, three and five years into the future, it is important to regularly capture ratio and rating information, at least annually.

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CHAPTER I: INTRODUCTION

"The Farm Credit System (FCS) is a nationwide network of borrower-owned lending institutions and specialized service organizations. Congress established the FCS in 1916 to provide a reliable source of credit for the nation's farmers and ranchers. The Farm Credit mission is to provide a reliable source of credit for American agriculture by making loans to qualified borrowers at competitive rates and providing insurance and related services" (Farm Credit System).

To fulfill this purpose, FCS lending institutions must meet the financing needs of a growing breadth of agricultural production business models. This includes everything from young, beginning, small (YBS) producers to large, corporate agribusinesses. Fulfilling this responsibility, while appropriately managing risk in an ever-increasing competitive environment, is challenging. At the organization level, FCS associations focus on risk-based lending in accordance with FCS guidance, including the application of core capital direction set forth in the Basal Accords. At the client level, the rating of risk assists FCS retail staff in loan approval, risk-based pricing, and expected loan-loss allowance decisions. FCS associations, within the flexibility allowed by the Farm Credit Administration, have developed models to analyze financial and related customer information in determining qualitative and quantitative risk measures.

Previous research has identified that the most effective ratios aligning with prediction of loan default are related to liquidity, solvency and repayment capacity. Successful farmers and ranchers tend to hold a moderate level of liquidity and solvency so that they are able to withstand the increasing volatility inherent in modern production agriculture. Additional emphasis is being placed on refining credit underwriting processes, enhancing enterprise risk management and strengthening product and service delivery models.

The objective of this thesis is to examine empirical customer account data from 2006-2012 to review the probability of default (PD) rating methodology used within the risk rating system implemented by a FCS association for production agricultural accounts. Even more, this analysis provides insight into the effectiveness of this methodology in predicting the migration of accounts across the association's currently-established PD rating categories with such migration being a precursor to actual loan default. Gaining a deeper understanding of PD rating migration and the robustness of the ratios used in determining PD rating enhances the ability of FCS institutions to fulfill their mission in providing reliable financing to American agriculture.

CHAPTER II: LITERATURE REVIEW

A wide range of research has been completed over the past few decades to establish and review various models for assessing risk for agricultural lending institutions. Those most applicable for the purposes of this paper are included in the ensuing discussion.

Featherstone, Roessler, and Barry conducted a study in determining probability of default and risk-rating class for Farm Credit System loans. In this paper, "risk rating class is studied for 157,853 loans in the Seventh Farm Credit District portfolio" (Featherstone, Roessler and Barry). At the time this research was completed, the Basel Accords had suggested the need for more "granularity" in classifying risk-ratings and overall improvement to existing systems. More complex rating methodologies in place at the time consisted of dual ratings that dealt with both the probability of default as well as the estimated loss given default. Since nearly all lending institutions use systems for rating risk, the objective of this article was to develop a consistent risk rating system using actual data from the loans made within the Seventh Farm Credit District (Featherstone, Roessler and Barry). Since the analysis was completed using historical ratios taken at loan origination, the predicted default probability was matched against the actual subset of loans that defaulted to assess the robustness of the model.

Featherstone, Roessler and Barry indicate that basic financial standards assessed at the 7th Farm Credit District were repayment capacity, solvency, liquidity, and collateral adequacy. When a potential borrower applies for a loan, staff evaluates the financial strength of the borrower by reviewing his/her earnings history and capital position as they compare to defined minimum underwriting standards. Though other, less-measurable factors play into the decision, meeting all of the underwriting standards typically qualifies the applicant for approval (Featherstone, Roessler and Barry). The specific ratios used in their study, and subsequently used by others, are repayment capacity percentage, owner equity percentage and working capital percentage. Commitment amount was also included in the regression with a secondary objective to test its significance in affecting loan class migration, along with loan type.

Results of the analysis indicate that all of the variables were statistically significant in predicting a majority of the loans that went into default. Commitment amount was not statistically significant in influencing default. Loan type showed statistical influence from owner equity in real estate loans only, while it was found that repayment capacity was an important factor to consider for operating loans. Further research should be done to look at the migration of loans from one risk-rating class to another over time and to look also at the incorporation of the loss given default component of the dual risk rating (Featherstone, Roessler and Barry).

In 2003, Haverkamp completed a thesis on the credit quality of Kansas farms. By relying on data obtained from the Kansas Farm Management Association for the years of 1980 through 2003, yearly financial ratios were calculated and applied to a credit scoring model previously developed by Featherstone, Roessler, and Barry. This was done with the objective of examining credit rating migration across periods of time.

Since credit risk is important to lenders, there has been a continuous effort in recent years across the agricultural lending industry to improve measurement of risk for the purposes of standardized decision-making and risk-based pricing. Haverkamp discusses the flexibility allowed in risk rating systems used by lenders and the accompanying weighting applied to the various components of the models used in determining ratings of the financial health of borrowers. "The result of utilizing the migration concept allows a richer, more comprehensive perspective on credit risk and loan losses than relying solely on the measurement of historic default rates" (Haverkamp). In absence of a rating system to rely upon, Haverkamp uses the well-established S&P rating system.

His study found that credit ratings stayed constant across multiple observation periods a majority of the time, consistent with results from previous studies. Further conclusions were made in the assessment of migration over longer periods of time, indicating a greater movement in ratings than over the short term, implying that loan length should be considered when determining loan pricing (Haverkamp). Another aspect of this research is the comparison of default probability for different farm types and regions in the state of Kansas demonstrating the importance in examining these factors as well.

Closely related to the research of Featherstone, Roessler and Barry is that of Jouault and Featherstone who used a logistic regression analysis with financial information from loan origination data from a French bank. Rapid change of the conditions of the agricultural industry, including the aggressive pace of technology adoption, has shifted risk from production to financial and required an increased need to develop credit risk models (Jouault and Featherstone). The paper makes interesting comparisons between the Anglo-American and European financial reporting models in addition to further definition of the multi-rating system to determine expected loss.

Results from Jouault and Featherstone’s analysis conclude that leverage is higher for defaulted loans, there is little difference in profitability between defaulted and non-defaulted loans, non-defaulted loans are greater in commitment amount, and loan length statistically increases default likelihood. Furthermore, the research confirms that leverage, profitability and liquidity are important in predicting probability of default (Jouault and Featherstone).

Financing decisions of lenders can also be based on information outside of quantitative measures. Featherstone, et al. conducted a survey and analysis to determine factors affecting the agricultural loan decision-making process for financial institutions in Kansas and Indiana (2007). In this study, agricultural lenders provided responses to simulated applications along with other information about themselves and the organization for which they worked. They concluded that both financial condition and character are important in the loan evaluation process. They also saw these factors playing a greater role in pricing decisions as well, noting that “interest rate differences based on credit quality are wider than in the past” (Featherstone, et al.).

In addition to methodology for assessing risk in agricultural lending institutions, additional research has been completed to determine the most meaningful financial ratios to monitor progress of agricultural production operations. In 2006, Mark Winger completed a thesis analyzing financial ratio benchmarks for Kansas farms from 1995 to 2004. Financial ratios are important to both producers and agricultural lenders because they allow the analyst to compare operations of differing sizes as dollars are converted to ratios or percentages. This provides the opportunity for the producer to benchmark themselves against other farmers and also assists lenders in establishing parameters for rating risk when considering approval of loan applications (Winger).

As agricultural lenders develop and refine their models for assessing credit risk, an understanding of financial characteristics that most accurately predict the success of a farm business or to identify warning signs of added financial risk, is important. This is also important to the producers driven toward success. Financial ratio analysis assesses both trends and comparative considerations, and is dedicated to “provide an indication of the capacity of the business to withstand risk” (Winger). Winger describes the makeup of ratios considered in the analysis, relying upon guidance from the Farm Financial Standards Council and financial tools created for the use of customers within an FCS association. He also describes the fourteen-point risk rating system used by U.S., AgBank, FCB, which has similarities to those used in other FCS associations.

Results of Winger’s analysis confirm, consistent with prior research, that financial ratio benchmarks are effective in assisting the producer to direct their business toward success. In testing the claim of prior research that there is a point where additional solvency and liquidity will decrease profitability, Winger discovers that the most profitable farms have moderate liquidity and solvency levels (Winger). He also finds that repayment capacity is quite variable from one year to another and should be considered as a trend over multiple years. The risk rating system of AgBank was shown to be dynamic in its ability to capture changes to risk and the benchmarks tested were supported in their robustness by the research (Winger) .

As stated in the research of Featherstone, Roessler and Barry, the need to conduct further research on the migration of an account’s risk rating over time is partially fulfilled through the objectives of this paper. This also includes a review of some financial ratios reviewed by Winger in their effectiveness as components of the association's probability of default rating models for production agriculture.

CHAPTER III: THEORY

Over the past decade, FCS institutions have enhanced their processes for assessing the risk of loan assets. The system has improved the clarity and consistency in risk assessment as they relate to credit risk and capital adequacy. In the agricultural lending industry the "building block for quantifying credit risk is Expected Loss (EL), the loss that can be expected from holding an asset" (Jouault and Featherstone). The association providing data for this analysis further defines EL as an estimate of loss inherent in the next twelve-month time horizon, based on the combined risk rating method using the components of both Probability of Default (PD) and Loss Given Default (LGD). Exposure at Default (EAD) is an additional component used by the association and also discussed in the research of Featherstone, Roessler, and Barry.

PD is defined as the likelihood a customer will experience default within the next twelve-month time horizon. FCS institutions use a 14-point PD-rating scale. LGD is the assessment of potential loss assuming a loan goes into default. The association in this study uses a four letter default scale of B (well-secured), D (adequately-secured), E (marginally-secured) and F (under-secured). EAD is the estimated loan volume the association could be exposed to for potential loss based on anticipated commitment utilization at default.

This analysis focuses on the PD rating component of the risk rating system for the association; therefore the internal procedures relating to it are further defined. The 14-point PD rating scale aligns with the Uniform Classification System (UCS) employed by the Comptroller of the Currency, Federal Reserve, Federal Deposit Insurance Corporation and the Farm Credit System. UCS credit classifications are assigned on the basis of risk and include the following five categories: Acceptable, Other Assets Especially Mentioned (OAEM), Substandard, Doubtful, and Loss (Farm Credit Administration). PD ratings and UCS designations are applied as follows.

PD ratings of one through three are reserved for acceptable loans with public debt ratings of A or better. PD ratings four through nine are classified Acceptable while the PD rating of 10 is classified as OAEM (Table 3.1). All acceptable loan assets are of the highest quality and include government-guaranteed loans. OAEM assets are still protected but are potentially weak, being criticized but not considered adverse.

Table 3.1: UCS Classifications and PD Ratings

UCS Classification	PD Rating
Acceptable	4 - 9
OAEM	10
Substandard - Accrual	11
Substandard - Non-Accrual	12
Doubtful	13
Loss	14

Adverse asset ratings begin with the PD rating of 11 which is classified as Substandard-Accrual, while a PD rating of 12 is classified Substandard-Nonaccrual. Substandard loans are inadequately protected by the repayment capacity, equity, and/or collateral pledged. They are characterized by the distinct possibility that the lender will sustain some loss if the deficiencies are not corrected. PD ratings of 13 are classified as Doubtful and have all the weaknesses inherent in those classified Substandard with the added characteristics that weaknesses make collection or liquidation in full, on the basis of currently existing facts, conditions, and values, highly questionable and improbable. The final PD rating of 14 is classified as Loss and considered uncollectible and that the asset is of such little value that continuance as a bookable asset is not warranted. Though recovery is not impossible, it is not practical or desirable to defer writing off the assets that have reached this classification.

The association complies with a consistent method for determining PD rating at the account level, based on specific risk components. Each component is given a score between 4 and 12 based on established ratio thresholds and then a weighting is applied to arrive at a weighted average for the overall PD rating. For example, a current ratio between 1.10 and 1.19 yields a component score of 9 that is multiplied by a weighting of 25% for a component contribution of 2.25. This component score is added to the remaining component scores of the model to arrive at the overall calculated PD rating. For the purposes of consistent risk analysis, the association strives to rely on calculated PD ratings, although deviation between calculated and what is finally assigned is sometimes necessary to adequately assess the risk of a given account. For the business models and commodity groups categorized as production agriculture, six components make up the gross score (Table 3.2).

Table 3.2: PD Rating Model Example

Component	Rating	Weight	Score
Industry	8	5%	0.40
Management	7	15%	1.05
3 Yr Avg DCR	8	20%	1.60
Current Ratio	9	25%	2.25
D/A Ratio	6	15%	0.90
3 Yr Avg GP / TL	7	20%	1.40
	Gross	Rounded	Assigned
Score	7.6	8	8

Two components are subjective in nature, one that assesses the adequacy of management as measured by the analyst’s judgment. For this category, analysts consider production, processing, marketing and financial management to determine subjective rating assigned. The other subjective measure is designed to account for the varying risk of the industry to which the account belongs. This score is typically assigned by the association based on market conditions and updated multiple times annually. The remaining components are objective measures of the following ratios:

Current Ratio (CR): Calculated by dividing total current assets by total current liabilities as a measure of liquidity.

Debt to Asset Ratio (D/A): Calculated by dividing total liabilities by total assets as a measure of solvency.

Gross Profit to Total Liabilities Ratio (GP/TL): Calculated by dividing a three year average of gross profit (two historical years plus a projection) by total liabilities as recorded on the most recent financial statement.

Debt Coverage (DCR): This is calculated by dividing a three year average of Adjusted EBITDA (two historical years plus a projection) by projected annual debt service (principal and interest). Adjusted EBITDA for a given year is calculated by deducting income taxes and distributions from EBITDA (Earnings before interest, taxes, depreciation and amortization) to arrive at the net cash earnings available for debt service.

Each of the ratio-based components are assigned a rating based on association-determined thresholds as shown in Table 3.3. When the current production agriculture risk rating model was adopted by the association, the component thresholds were determined from generalized industry standards.

Table 3.3: Ratio-based PD Model Component Thresholds

Rating	DCR	CR	D/A	VFP/TL
4	>= 2.50	>= 2.50	<= 20%	>= 95%
5	>= 2.00	>= 2.00	<= 25%	>= 85%
6	>= 1.60	>= 1.75	<= 30%	>= 75%
7	>= 1.40	>= 1.40	<= 35%	>= 70%
8	>= 1.20	>= 1.20	<= 40%	>= 65%
9	>= 1.10	>= 1.10	<= 45%	>= 60%
10	>= 1.00	>= 1.00	<= 50%	>= 50%
11	>= 0.90	>= 0.90	<= 60%	>= 45%
12	< 0.90	< 0.90	> 60%	< 45%

Although the adoption of standardized thresholds has served its purpose, the association is interested in using empirical data to review and better understand key drivers of PD rating migration.

CHAPTER IV: METHODS

Customer financial data with multiple years for comparison is necessary for the appropriate review of PD ratings and their changes over time. This provides the basis for analysis in understanding the financial metrics of the association portfolio while also sourcing the variables required for regression analysis of component ratios used in generating the PD ratings.

4.1 Description of Dataset

The data used for the analysis is from customer-level financial information recorded in the association's financial analysis software designed to record balance sheet, earnings statement and annual debt repayment data. The financial information was obtained from the analysis software database and combined with PD ratings assigned to each account as recorded in another software application designed to record customer relationship management, loan accounting and loan origination data.

The original dataset contained a total of 86,325 observations from the years 2006 to 2012 consisting of various fields of data beginning with customer name, numerical customer identifier, balance sheet date, earnings statement date, and PD rating as of the statement date.

Data elements associated with the balance sheet include: cash and equivalents, accounts receivable, inventory, crops, other current assets, total current assets, property, plant and equipment, other non-current assets, real property, total non-current assets, total assets, accounts payable, operating line of credit, CCC loans, accrued rent and taxes, accrued interest, current portion of long term debt, deferred taxes, other current liabilities, total current liabilities, notes payable, capital leases, mortgages payable, other non-current liabilities, total non-current liabilities, and total liabilities.

Data elements associated with the earnings statement and annual debt repayment analysis include: agricultural program payments, total farm income, cost of goods sold, production livestock purchases, accrual income adjustments, gross profit (value of farm production), chemical expense, custom hire, feed, fertilizer, freight/trucking, gas/fuel/oil, term debt interest, operating interest, rent/lease, seed, storage, other expense, total farm operating expense, net farm earnings, gain/loss from capital assets sales, net earnings after gain/loss, gross non-farm income, non-farm non-interest expense, non-farm interest expense, total non-farm expenses, net non-farm income, total net earnings, income/social security tax expense, family living/distributions, total earned net worth change, adjusted EBITDA, unfunded capital expenditures, and debt payments.

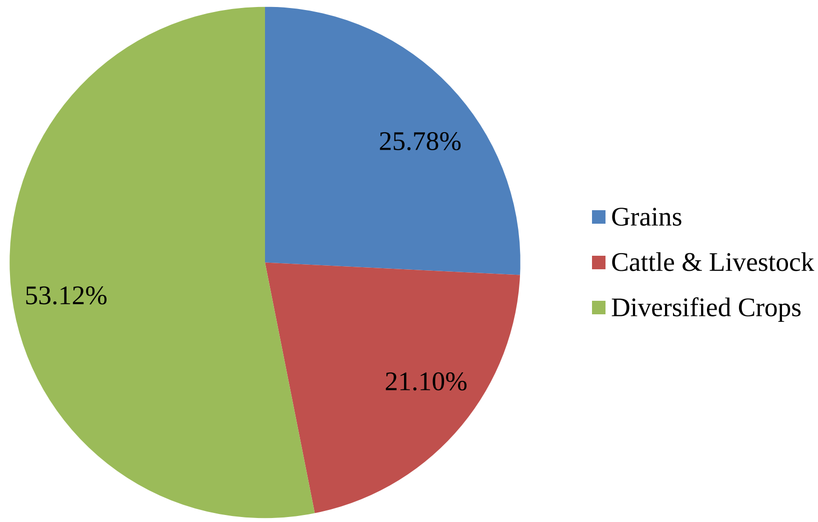
From the original dataset, observations that did not fit the criteria of following the association-defined production agricultural business model were removed for consistency with the objective of this thesis. Those loans removed were: Ag processing, Ag Services, Communications, Consumer, Energy, Dairy, Forest Products, Investors, and Landlords. These business types are rated based on a different PD rating criterion, due to the unique natures of their business models.

As defined by the association, observations classified as production agriculture include the commodity types shown in Figure 4.1. Observations associated with these business types are used in the analysis. Once the non-production agriculture business observations were removed, additional steps were taken to ensure the most accurate sample of data was used.

Only those customers with two or more years of data were included in the analysis. This was determined by focusing on the dates of the earnings information. To account for the variability in timing of the receipt of customer earnings data, a 60-day window of time beyond the date of the previous year earnings statement was allowed to determine the span of the observations and to which year the data should be assigned. According to this method, any observations that remained with duplicated balance sheet and/or earnings statement values were then deleted. All observations with zero values for current assets, current liabilities, gross farm income and adjusted EBITDA were also removed from the dataset. Assuming that the omissions were a result of incomplete information received from the customers, they were deleted so that all observations contained the data necessary for the full calculation of all ratios for the analysis.

Upon completion of all steps, the original data set of 86,325 observations was reduced to 17,943 for the seven year period. The two most prominent business types of grains and cattle/livestock make up 46.9% of all observations (Figure 4.1). A variety of other diversified crops grown throughout the association lending area round out the dataset. The business models related to the commodity types included are similar enough that the association uses the same PD rating methodology to assess their risk.

Figure 4.1: Distribution of Commodity Types for All Observations



In addition to analysis on the dynamics of the PD ratings and component ratios, OLS regression was used to analyze the data to see how the current period PD rating and component ratios (described below as independent variables) affected the PD rating one year, three years and five years out.

4.2 Definition of Variables

4.2.1 Dependent Variable

Future PD Rating: Represents the assigned PD rating for the observed farm either one, three or five years into the future.

4.2.2 Independent Variables

Current PD Rating: Represents the assigned PD rating for the given observation, based on the subjective and objective scoring components previously described. The 14-point scale rating is expected to demonstrate the likelihood a customer will experience default within the next twelve-month time horizon.

Current Ratio (Inverse): The current ratio is calculated by dividing current assets by current liabilities. This ratio is an indication of the extent to which current farm assets, if liquidated, would cover current farm liabilities (Farm Financial Standards Council). It assesses the adequacy of the operation's second line of defense if price cyclicality negatively affects the ability of annual farm earnings to pay expenses and/or debt service requirements. For this analysis, the inverse of this ratio (current liabilities divided by current assets) is used to reduce the range of ratio values while still maintaining appropriate variation.

Debt to Asset Ratio: Debt to asset ratio is calculated by dividing total liabilities by total assets. This ratio expresses what proportion of total assets is owed to creditors and represents the risk exposure of the business (Farm Financial Standards Council). It is considered as a tertiary line of defense when earnings and liquidity are insufficient to meet annual expense and debt service obligations.

Gross Profit to Total Liabilities Ratio: In contrast to the model definition of using a three-year average of gross profit, this analysis is calculated using current year gross profit by current year total liabilities from the dataset. The nature of the information available for the calculation required this approach which is considered acceptable in understanding the influence of this variable on future year PD ratings. Though not included as one of the ratios recommended by the Farm Financial Standards Council, the use of this ratio is to compare the earnings capability of the operation against its total capital debt obligations.

Debt Coverage (Inverse): As noted in the theory section of this thesis, the association agrees with Winger's claim that the cyclicality of commodity prices suggests that the utilization of multi-year average earnings is most appropriate in calculating debt coverage. However, due to limitations in the dataset, current year Adjusted EBITDA and current year annual debt service is used.

Furthermore, to reduce the variability that flexible debt structuring across accounts could pose, annual debt service for each observation was derived by amortizing the sum of all term debt over ten years at a five percent interest rate. The debt coverage ratio demonstrates how well the operation is able to meet annual debt servicing requirements with the earnings that remain after all other expenses are paid. Although this ratio is typically calculated by dividing adjusted EBITDA by debt payments, the inverse of this ratio (current debt service divided by current Adjusted EBITDA) is used to reduce the range of ratio values while still maintaining appropriate variation.

Not included as component ratios for the PD model calculations currently, this analysis reviews an alternative liquidity ratio of Working Capital to Gross Profit. Funded Debt to EBITDA is also considered as an alternative to Gross Profit to Total Liabilities.

Working Capital to Gross Profit: Calculated by dividing working capital by gross profit and gives the relationship of the working capital to the size of the farm business (Farm Financial Standards Council).

Funded Debt to EBITDA: Calculated by dividing the total of all interest-bearing debt to by Earnings before Interest, Taxes, Depreciation, and Amortization (EBITDA). Though not included as one of the ratios recommended by the Farm Financial Standards Council, the intention of this ratio is to compare the net earning capability of the operation against its funded debt obligations. It could be seen as an alternative to the

Gross Profit to Total Liabilities previously mentioned as an indicator of earnings generation of the operation against its total capital debt obligations.

4.3 Regression Model

OLS Regression is the method used for determining the statistical significance of the PD ratings and described ratio components for this analysis. It is expected that the initial PD rating in any given year would have a positive relationship, and be statistically significant in estimating future PD ratings. The component ratios would be expected to affect future PD rating as described hereafter.

The inverse of the current ratio (CR(i)), as a financial liquidity measure, is expected to have a positive relationship with PD movement. As an operation has more liquid asset reserves, it is able to better absorb earnings fluctuations and decrease the risk of default to the lender. Therefore, the increased CR is expected to cause an increase in PD rating.

The working capital to gross profit ratio (WC/GP) is an alternative liquidity measure expected to have a negative relationship with PD movement and the same hypothesis structure as the current ratio. The more working capital an operation has compared to gross profit, the more able it is supplement earnings deficiencies with cash reserves and decrease risk (PD rating) to the lender.

The debt to asset ratio (D/A) is a commonly used measure of leverage and solvency that is expected to have a positive relationship with PD rating. As the total liabilities of a business decrease in proportion to total assets, the risk of default also decreases and is represented by a reduction in PD rating.

Both the gross profit to total liabilities (GP/TL) and the funded debt to EBITDA (FD/EBITDA) ratios are designed to compare balance sheet liabilities to the income generating ability of an operation. Though both take a slightly different approach, the comparison is similar. It is expected that gross profit to total liabilities would have a negative relationship with a future PD rating. As total liabilities decrease compared to gross earnings, the ratio increases and risk of loan default should decreases as shown in a lower PD rating. In contrast, FD/ EBITDA would have a positive relationship with future PD rating. As this ratio gets higher, it represents a greater deficit between total debt and the earnings available to service it. Thus, a higher ratio would put upward pressure on risk and the PD rating that is designed to represent the greater risk.

The inverse of the debt coverage ratio (DCR(i)) is a measure of debt repayment capacity and expected to have a positive relationship with future PD rating. As the ratio of required debt payments compared to earnings available to service debt increases, the less protected the operation is from default. Therefore, higher inverse DCR yields a higher PD rating.

CHAPTER V: ANALYSIS AND RESULTS

Further defining the breakdown of the 17,943 observations, the summary information for mean, standard deviation, minimum and maximum are provided in Table 5.1. The distribution of PD ratings, along with their migration over the time period covered by the dataset are important factors in assessing risk rating methodology. Further, a look at the component ratio distribution and regression analysis results provides important insights into the rating effectiveness.

5.1 Analysis

With an average of 2,563 observations per year, the mean probability of default rating for all observations was 6.41 supporting the association's strategy for quality customer acquisition and maintenance (Table 5.1). Although business development goals will allow for consideration of new customer acquisition up the PD-8 level with cyclicality pushing existing accounts beyond that level at times, maintaining an average PD 6-7 for the entire association aligns with the overall portfolio strategy.

Table 5.1: Summary Statistics for Agricultural Loans from a Farm Credit Association, 2006-2012

Ratio	Mean	Standard Deviation	Min	Max
Number of Observations per Year	2,563	505.72	1,570	3,102
Probability of Default Rating	6.41	1.64	4.00	13.00
Inverse Current Ratio	0.62	2.01	0.00	52.28
Working Capital to Gross Profit	0.68	1.85	-20.00	20.00
Debt to Asset	27.00%	16.60%	0.00%	81.46%
Gross Profit to Total Liabilities	2.10	6.90	0.00	103.00
Funded Debt to EBITDA	3.15	10.10	-100.00	100.00
Inverse Debt Coverage Ratio	0.42	2.69	-38.72	39.92

Most of the ratios show minimums and maximums above zero, with the exception of WC/GP, FD/EBITDA and DCR(i) which rely on liquidity measures or net earnings figures (post-operating expenses) that can yield negative results. To enhance effectiveness of the analysis, outliers were "fenced" using the method employed by Featherstone, Roessler, and Barry and Haverkamp. All outlying values were adjusted to be within three times the standard deviation above and below the mean of the ratio (Featherstone, Roessler and Barry). The statistics included in Table 5.1 show the mean, standard deviation, minimum and maximum after applying the fencing methodology.

The distributions of each ratio are included the figures below based on the currently established component thresholds from Table 3.2, as well as the full distribution based on wider parameters.

Figure 5.1.1: Percentage Distribution of Inverted CR Based on Current Thresholds

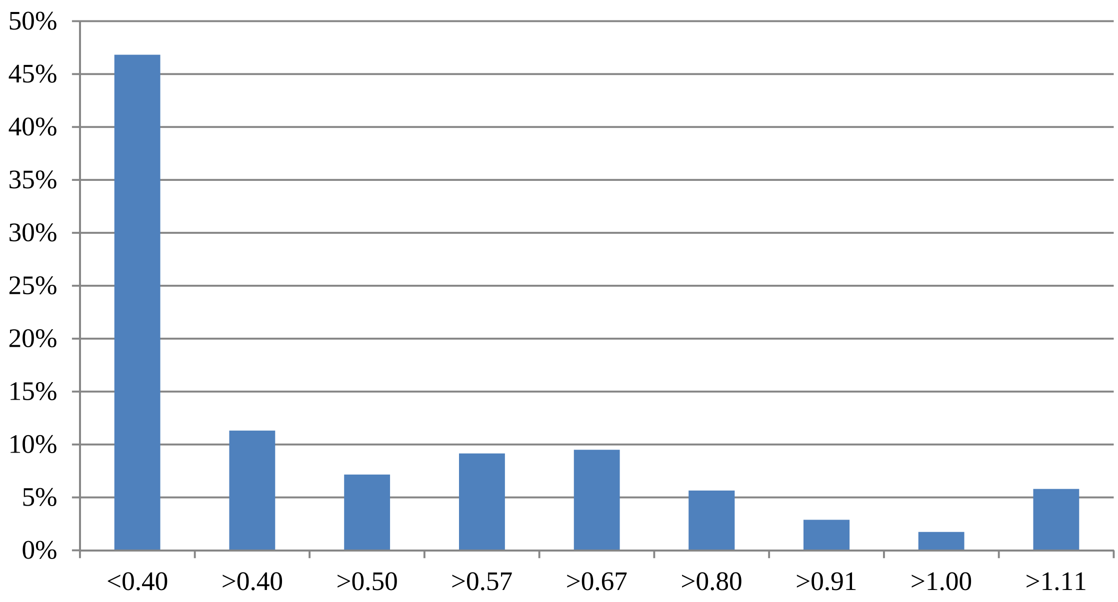
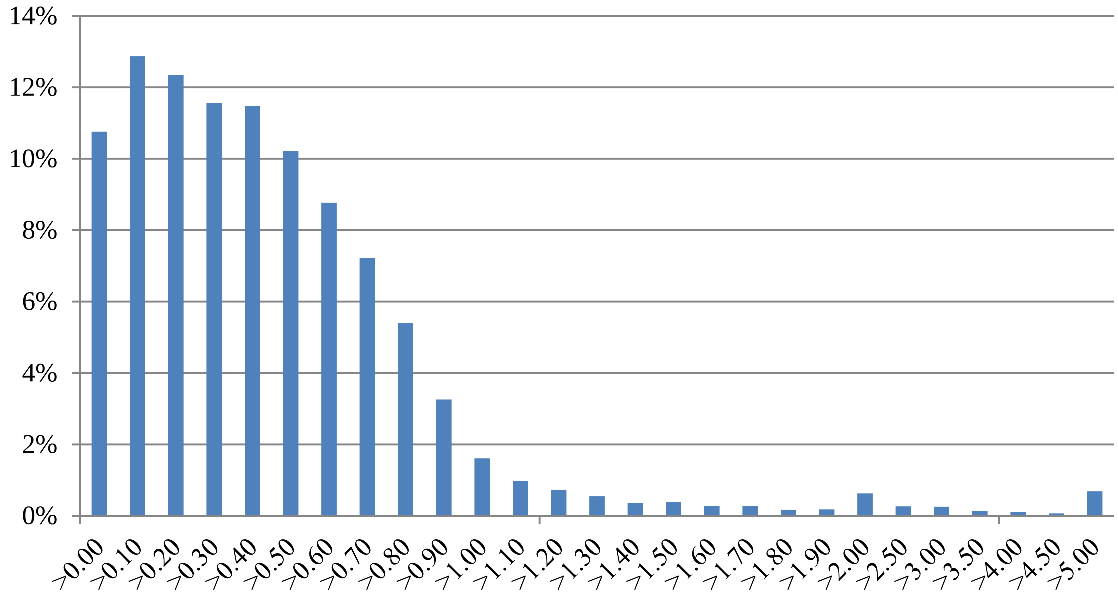


Figure 5.1 shows a high percentage of observations lying below the minimum threshold in the current model. Barring the possibility that the data available to calculate this ratio is incomplete, the distribution suggests that reconsideration of the thresholds may be

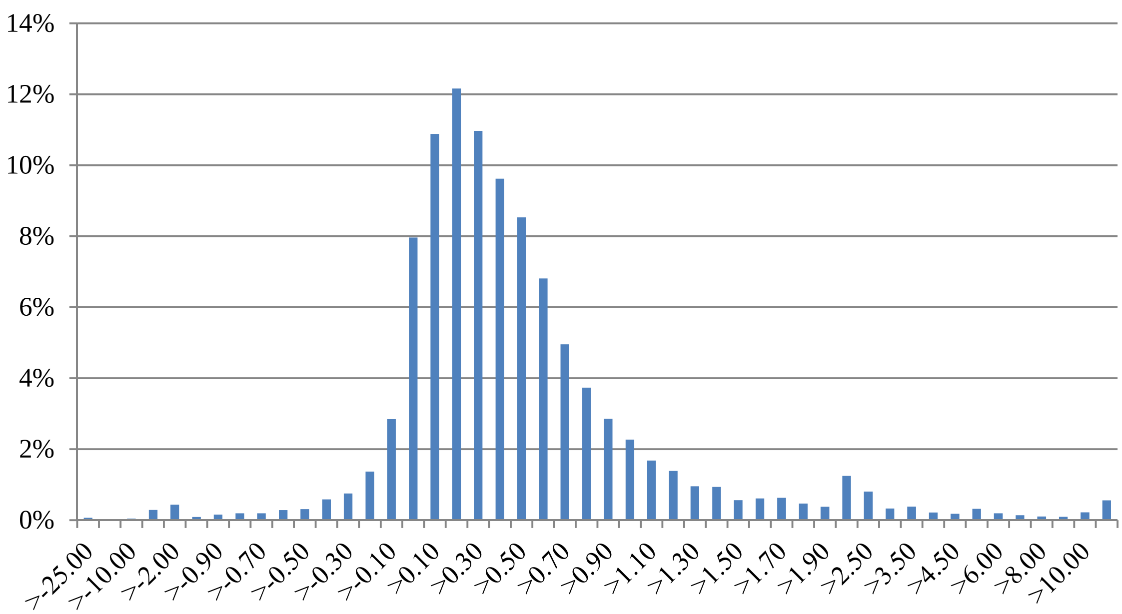
warranted. In Figure 5.2, the full distribution is shown to represent how many observations lie outside of the currently established thresholds.

Figure 5.1.2: Percentage Distribution of Inverted CR with Widened Parameters



Not currently used in the model or conforming to a previously-decided set of thresholds, the alternative liquidity ratio of WC/GP shows a normal distribution in Figure 5.2.

Figure 5.2: Percentage Distribution of WC/GP



The series of figures showing the D/A and GP/TL ratio distributions demonstrate similar results as the inverted CR figures. A larger proportion of observations lie outside of the currently-established thresholds and are further explained in the wider distribution figures.

Figure 5.3.1: Percentage Distribution of D/A Based on Current Thresholds

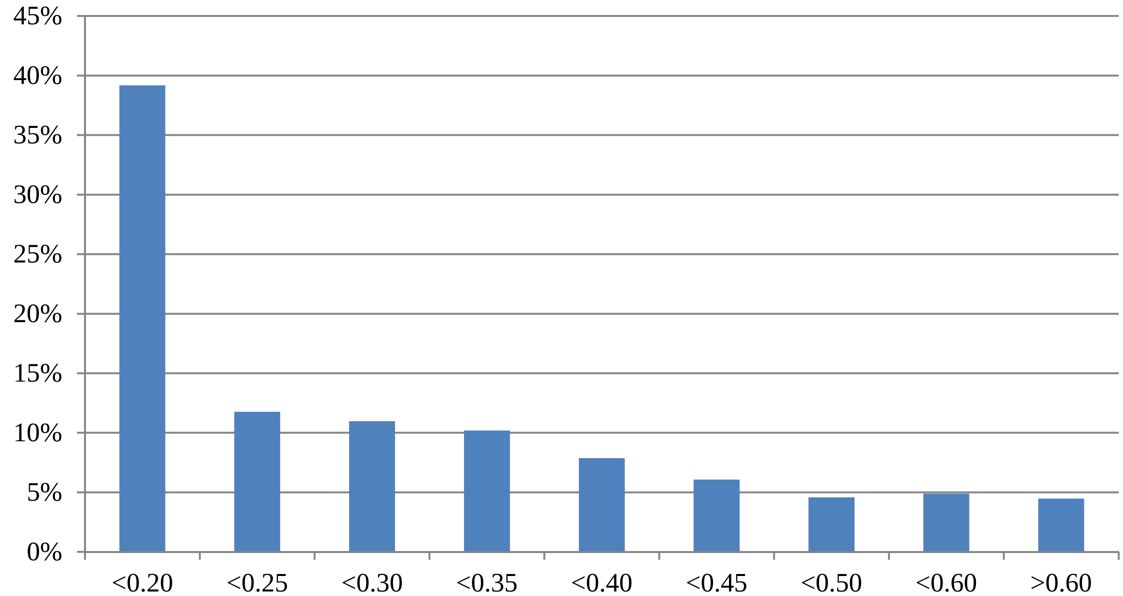


Figure 5.3.2: Percentage Distribution of D/A with Widened Parameters

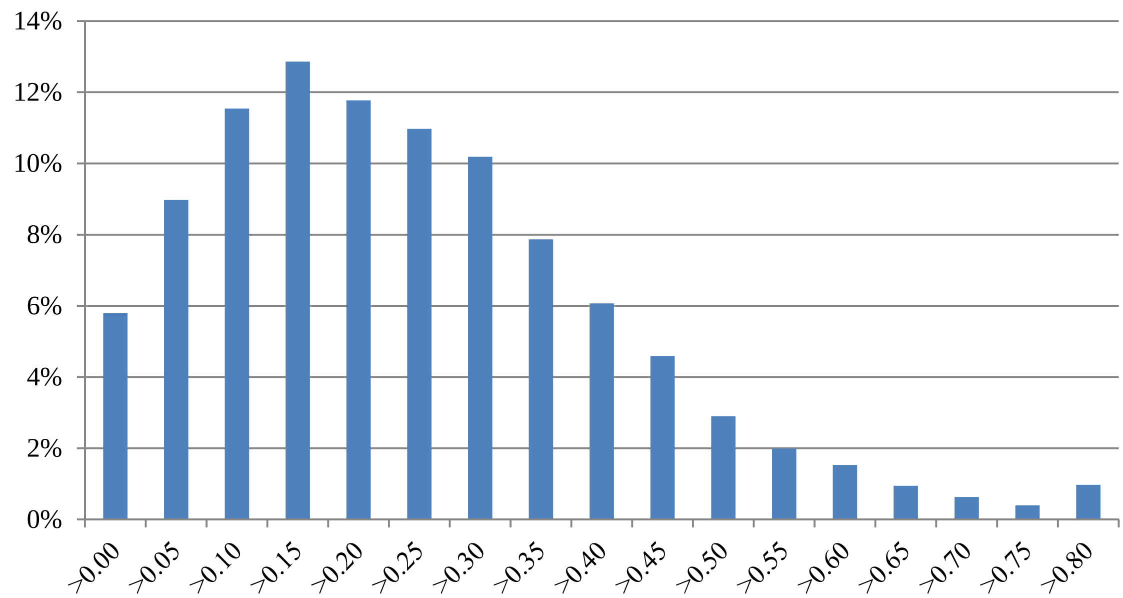


Figure 5.4.1: Percentage Distribution of GP/TL Based on Current Thresholds

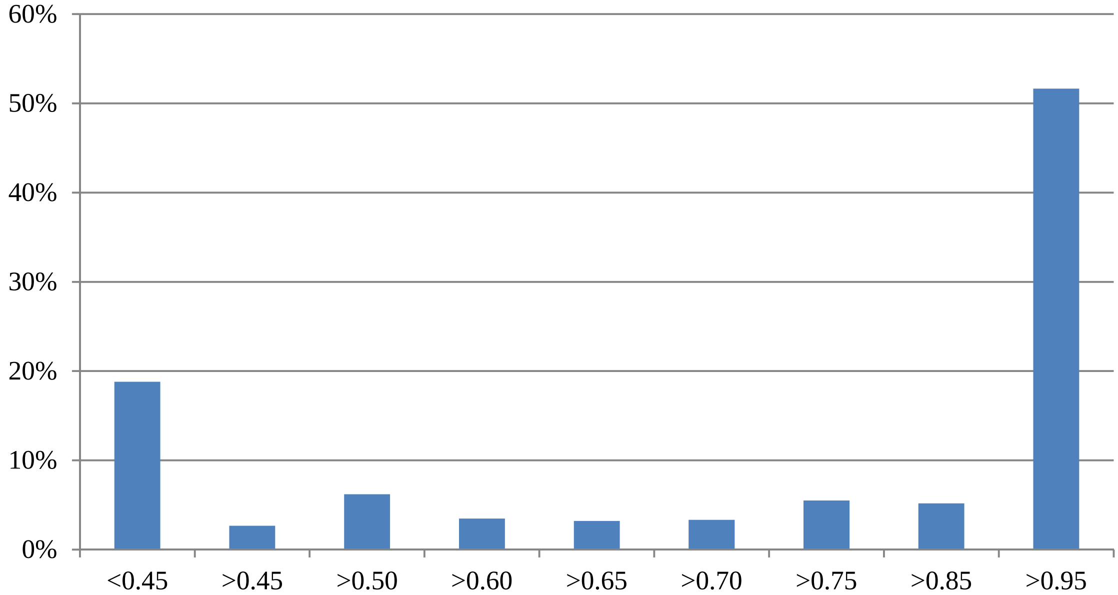
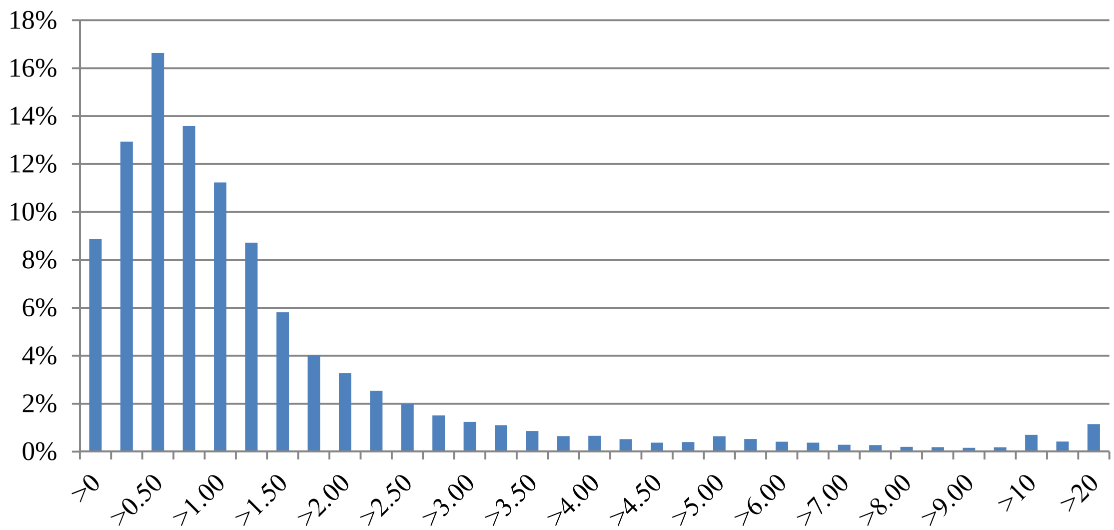


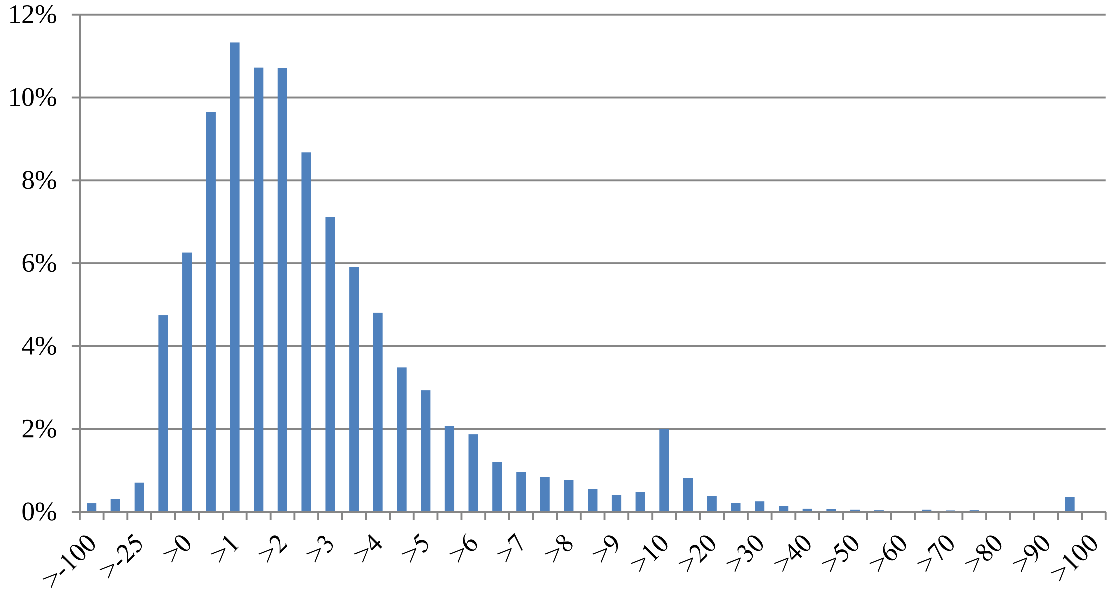
Figure 5.4.2: Percentage Distribution of GP/TL with Widened Parameters



Comparing the two figures for GP/TL, it is interesting to note that the high percentage of observations beyond 0.95 spread out in small increments of less than 2% of the distribution from 2.50 to beyond 20. Although the current thresholds appear to narrower than they should be, they still account for over 50% of all observations in the dataset.

Lacking established thresholds, Figure 5.5 shows that the alternative ratio of FD/EBITDA is distributed normally with the highest between the ratio yields of 0.5 to 2.5.

Figure 5.5: Percentage Distribution of FD/EBITDA



Consistent with the other thresholds, the inverted DCR displays similar outlying observations (Figure 5.6.1) which can be further explained in Figure 5.6.2.

Figure 5.6.1: Percentage Distribution of Inverted DCR Based on Current Thresholds

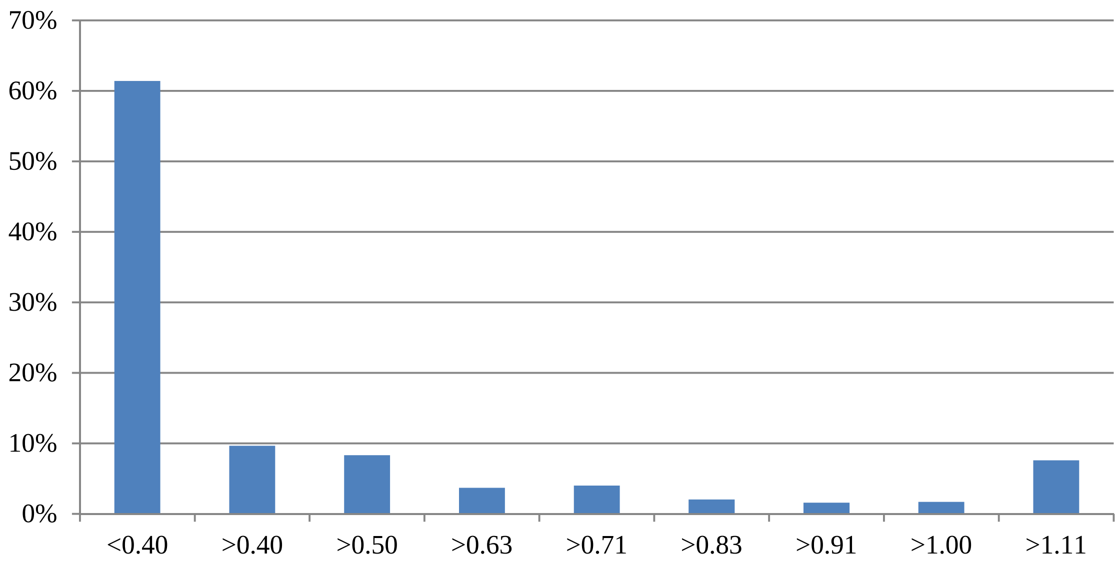
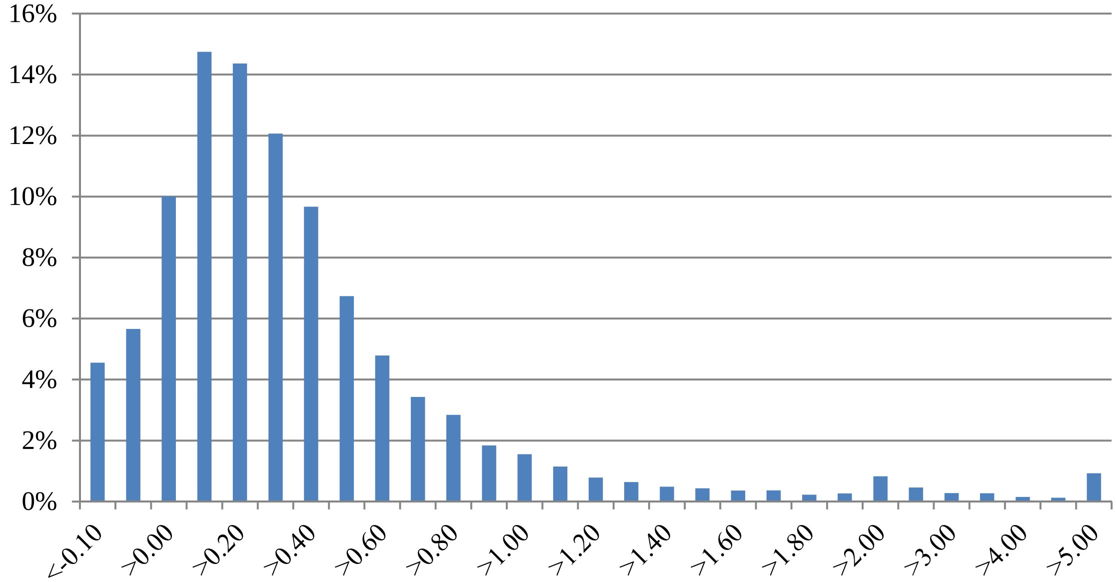


Figure 5.6.2: Percentage Distribution of Inverted DCR with Widened Parameters



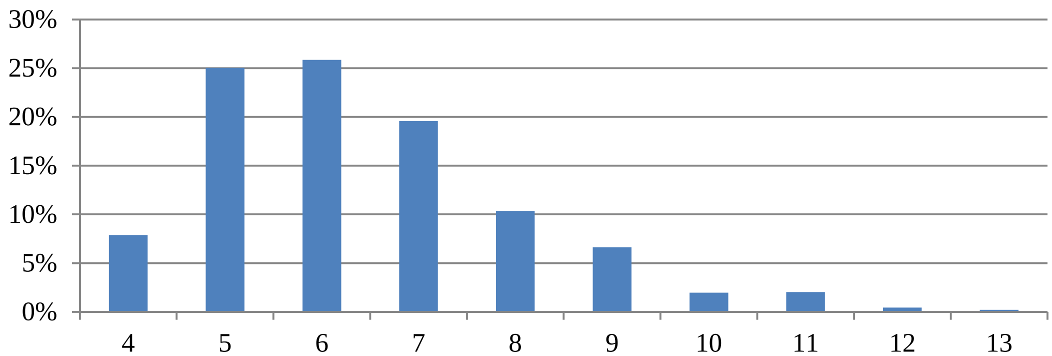
The distribution of component ratios currently in the PD model, with high percentages of values outside of the established thresholds, is not as expected. The information provided in the distribution graphs above are insightful as they suggest that the thresholds in place could be inadequate in explaining the full variation that exists in the components.

It is also noted that the dataset comes from information stored in the institution's financial analysis software. When the information is completed for use in credit decisions, it is imported from the analysis software into separate loan origination and accounting software. While the information imported into the origination and accounting software is always complete, information that exists in the analysis software alone can be incomplete. So, some of the information used in this analysis could have come from partially completed financial updates, causing less reliable results.

WC/GP has the smallest variation since the liquidity side of the ratio is more constant. FD/EBITDA has the largest variation based on the general price cyclicality of production agriculture and its effects on the annual earnings of production agriculture business models. Though it is measured on a year-to-year basis for this analysis, the association employs a three year average earnings figure for this measure attempting to minimize variation from inherent cyclicality.

The distribution of the PD ratings across all observations shows the largest number falling in the PD-6 classification, followed closely by the PD-5 group and then PD-7 (Figure 5.7). As mentioned previously, the portfolio strategy of the association strives to keep average PD ratings between PD-6 and PD-7. The averages are heavily influenced by 50% of all ratings falling within either the PD-5 or PD-6 categories.

Figure 5.7: Probability of Default Ratings for All Observations (2006-2012)



Business acquisition strategies can include PD-7 and PD-8 accounts that are considered profitable enough to move into the PD-6 category within a reasonable amount of time. On their way to lower risk levels, circumstances in a given year could push them into the PD-9 category or higher at which point customer solution teams work with customers to help them assess their progress toward the average.

The number of observations studied for each year varies from 1,570 in 2006 to 3,102 in 2010. Average probability of default rating also varies each year as shown in Table 5.2. The PD rating movement aligns closely with price cyclicality of commodities classified by the association as production agriculture. The trend from 2006 to 2012 would suggest a three to four year cycle of reversing movement in PD ratings which follows the typical commodity price cycles experienced by production agriculture in the region.

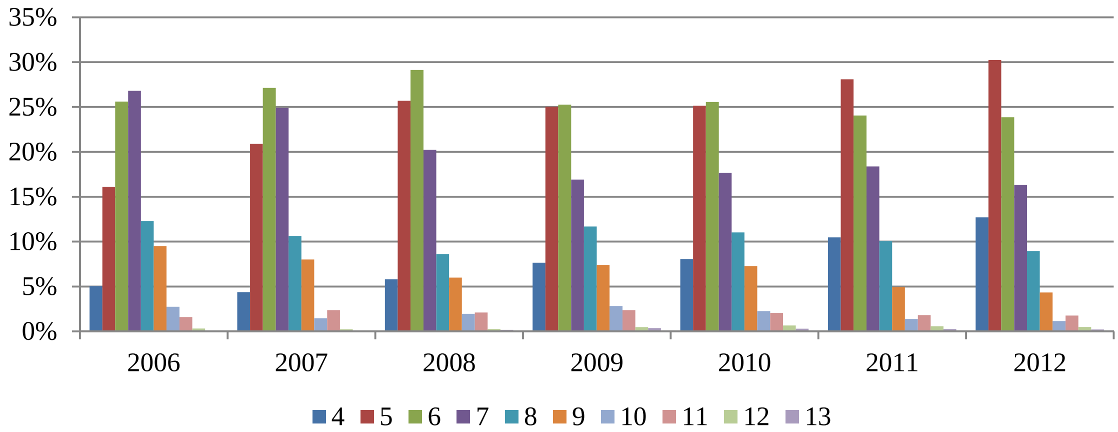
Table 5.2: Average PD Ratings and Standard Deviations by Year

Year	Average PD Rating	Standard Deviation	Number of Observations
2006	6.75	1.54	1570
2007	6.60	1.53	2197
2008	6.39	1.56	3003
2009	6.51	1.73	2968
2010	6.46	1.70	3102
2011	6.24	1.64	2656
2012	6.09	1.62	2447

Although this cycle can be determined by the effects of commodity quality and yield on ratios in the PD model, it is rare that such characteristics are able to significantly influence the wide geography of the association service area. Thus, the change in average PD ratings over time is typically attributed to commodity price variability associated with supply and demand and its effects on customers' PD model ratios. The standard deviation varies by year and is growing through the years, which could indicate increased risk in producing the commodities included in this study.

In addition to reviewing the average PD ratings, an evaluation of the change in PD rating distribution by year is included in Figure 5.8. Though the average PD rating stays fairly consistent through the years, the migration of distribution between ratings towards better quality classification is noted as a mitigating factor to the potential increase in volatility. That being said, the influence of commodity price cycles on the production agriculture businesses serviced by the association have had a positive effect on farmers and ranchers over the past 5 to 10 year period.

Figure 5.8: Distribution of Probability of Default Ratings by Year



The PD ratings 5-7 accounted for 67% to 75% of all observations each year, consistent with the risk strategy of the association (Figure 5.8). The distribution of observations within those three ratings consistently changed over time. In 2006, the PD-7 rating led the distribution with the PD-6 rating not far behind. The PD-6 rating was the highest in 2007 with a gradual change in distribution each year as the PD-5 rating was highest in 2011. Following suit, the PD-4 rating grew each year while the PD-9 consistently declined. The change in trends for the PD-8 rating, along with PD ratings 10-13, were less predictable through all years. This information suggests that while management of adverse assets was steady, the overall financial health of the association portfolio improved over the years.

With seven years of data, an analysis can also be done on the percentage migration of PD rating observations from one period to another. The tables below show the average transition rates for one, three and five years. The origin of this analysis comes from counting the number of observations, based on their initial rating, that either remained the same or changed one, three and five years into the future. The migration is then adjusted to show as a percentage of the total counted to each initial rating category. In general, the highest percentage of observations remains at the same PD rating level from one period to the other. Furthermore, the percentage of ratings that remains the same decreases as the observation timespan increases which is to be expected since the definition of probability of default is the likelihood of default occurring within the next 12-month time horizon.

Table 5.3.1: Average One-Year Transition Rates for All PD Ratings

Initial	PD Rating at t+1 (%)										
Rating	4	5	6	7	8	9	10	11	12	13	# Obs.
4	45.49%	36.27%	10.78%	5.88%	1.57%	0.00%	0.00%	0.00%	0.00%	0.00%	510
5	6.03%	60.53%	22.20%	8.47%	1.81%	0.77%	0.00%	0.18%	0.00%	0.00%	2,207
6	2.03%	10.97%	60.55%	20.83%	4.02%	1.42%	0.13%	0.04%	0.00%	0.00%	2,261
7	1.31%	4.75%	16.80%	54.22%	16.99%	3.75%	1.81%	0.37%	0.00%	0.00%	1,601
8	0.34%	2.99%	8.84%	22.16%	48.34%	14.12%	2.87%	0.23%	0.11%	0.00%	871
9	0.00%	0.95%	2.65%	11.15%	14.74%	61.44%	5.86%	2.84%	0.38%	0.00%	529
10	0.58%	1.73%	7.51%	11.56%	21.39%	11.56%	42.77%	2.89%	0.00%	0.00%	173
11	1.45%	1.45%	2.42%	7.73%	10.14%	6.28%	12.56%	56.04%	1.45%	0.48%	207
12	4.88%	0.00%	4.88%	7.32%	2.44%	0.00%	2.44%	36.59%	36.59%	4.88%	41
13	0.00%	0.00%	4.76%	4.76%	9.52%	0.00%	4.76%	23.81%	0.00%	52.38%	21

For those observations that migrate, it is more likely across all three tables that the PD 4-6 group moves to higher PD ratings than lower with PD-7 moving either direction. Consequently, the PD 8-13 group is more likely to move toward lower PD ratings.

Table 5.3.2: Average Three-Year Transition Rates for All PD Ratings

Initial	PD Rating at t+3 (%)										
Rating	4	5	6	7	8	9	10	11	12	13	# Obs.
4	21.19%	41.06%	23.84%	11.92%	0.88%	0.66%	0.22%	0.22%	0.00%	0.00%	453
5	7.48%	41.98%	30.63%	14.02%	3.02%	2.44%	0.14%	0.29%	0.00%	0.00%	1,391
6	3.38%	17.85%	40.17%	25.71%	9.43%	2.36%	0.79%	0.31%	0.00%	0.00%	1,272
7	1.58%	9.26%	25.94%	34.96%	17.78%	7.80%	1.83%	0.85%	0.00%	0.00%	821
8	0.82%	5.77%	15.88%	29.69%	28.45%	12.99%	5.57%	0.82%	0.00%	0.00%	485
9	0.65%	3.27%	10.46%	22.88%	16.34%	37.58%	5.23%	3.59%	0.00%	0.00%	306
10	0.00%	7.55%	19.81%	26.42%	17.92%	13.21%	13.21%	1.89%	0.00%	0.00%	106
11	0.85%	8.47%	6.78%	14.41%	16.95%	11.86%	14.41%	24.58%	1.69%	0.00%	118
12	6.25%	0.00%	6.25%	12.50%	18.75%	9.38%	15.63%	15.63%	15.63%	0.00%	32
13	0.00%	0.00%	14.29%	7.14%	35.71%	0.00%	7.14%	35.71%	0.00%	0.00%	14

Contrasting the results from assessing percentage PD rating movement one year into the future, the concentration of migration is wider when looking at the table representing migration 5 years out (Table 5.3.3). The number of observations per PD rating declines for the three and five year transition rates, given observations available in the dataset.

Table 5.3.3: Average Five-Year Transition Rates for All PD Ratings

Initial Rating	PD Rating at t+5 (%) 4	5	6	7	8	9	10	11	12	13	# Obs.
4	7.07%	43.43%	27.27%	18.69%	1.52%	1.52%	0.00%	0.51%	0.00%	0.00%	198
5	5.48%	32.88%	31.16%	19.86%	6.85%	3.25%	0.00%	0.51%	0.00%	0.00%	584
6	2.92%	17.71%	33.33%	32.50%	9.38%	2.71%	0.83%	0.63%	0.00%	0.00%	480
7	1.80%	8.08%	25.45%	39.82%	15.57%	6.59%	2.69%	0.00%	0.00%	0.00%	334
8	2.00%	5.33%	12.00%	40.00%	16.67%	14.67%	7.33%	2.00%	0.00%	0.00%	150
9	1.12%	3.37%	10.11%	26.97%	14.61%	33.71%	6.74%	2.25%	1.12%	0.00%	89
10	0.00%	7.14%	3.57%	25.00%	35.71%	28.57%	0.00%	0.00%	0.00%	0.00%	28
11	1.92%	1.92%	21.15%	13.46%	15.38%	17.31%	13.46%	15.38%	0.00%	0.00%	52
12	0.00%	0.00%	11.11%	66.67%	0.00%	11.11%	0.00%	0.00%	11.11%	0.00%	9
13	0.00%	0.00%	20.00%	20.00%	40.00%	0.00%	0.00%	20.00%	0.00%	0.00%	5

5.2 Results

Along with the review of PD ratings and their migration over the years is a detailed analysis of the PD rating components used as variables in an OLS regression model. Table 5.4.1 represents the average component ratios by PD rating in period t across all observations. The information in this table, along with regression analysis results, suggests effectiveness in predicting migration of PD rating.

Table 5.4.1: Average Ratios at Period t for Each PD Rating at Period t

PD_t Rating	Current Ratio (Inverse)	Working Capital to Gross Profit	Debt to Asset	Gross Profit to Total Liabilities	Funded Debt to EBITDA	Debt Coverage (Inverse)
4	0.22	1.15	13.49%	5.04	1.50	0.22
5	0.30	0.83	17.97%	3.38	1.68	0.25
6	0.62	0.79	25.51%	1.73	2.76	0.44
7	0.61	0.63	30.76%	1.22	4.26	0.52
8	0.74	0.45	36.44%	0.91	4.52	0.67
9	1.25	0.16	46.28%	0.67	4.85	0.63
10	1.01	0.31	41.04%	0.57	6.26	0.84
11	2.13	-0.25	39.65%	0.70	7.47	-0.13
12	3.95	0.14	50.75%	0.59	3.39	-1.06
13	3.55	0.03	66.28%	0.42	-6.47	0.04

In general, the average ratios in Table 5.4.1 follow expectations across the PD rating levels displayed. The inverted CR incrementally increases as the PD rating increases, with some variation in pattern. WC/GP also mostly follows the expected pattern until PD-10, at which point it fluctuates outside of expectations. This is also true with the D/A and inverted DCR. GP/TL and FD/EBITDA hold the expected pattern further into higher PD ratings.

In summary, all appear to hold incremental consistency from PD-4 to PD-8 (Acceptable classification). Inconsistencies in the pattern sometimes appear at the PD-9 level but more in the PD-10 ratings (OAEM classification) and higher (Substandard classifications). Since significant weaknesses in some of the ratios can heavily influence the assigned PD rating of an account, it appears that such influence can begin to negate strengths in other rating categories. More clearly stated, the incremental trend for each component ratio appears to be disrupted as an account moves into the higher risk classifications.

Table 5.4.2: Average Ratios at Period t for Each PD Rating at Period t+1

PD_{t+1} Rating	Current Ratio (Inverse)	Working Capital to Gross Profit	Debt to Asset	Gross Profit to Total Liabilities	Funded Debt to EBITDA	Debt Coverage (Inverse)
4	0.27	0.91	15.12%	4.44	1.53	0.21
5	0.34	0.75	19.72%	2.99	1.80	0.24
6	0.66	0.68	27.51%	1.55	3.39	0.44
7	0.66	0.55	32.16%	1.18	3.65	0.66
8	0.68	0.51	37.11%	0.87	3.88	0.71
9	1.14	0.15	46.50%	0.71	5.88	0.54
10	1.19	0.42	38.88%	0.68	3.19	1.21
11	1.78	0.11	37.57%	0.64	8.17	0.13
12	0.91	-0.11	47.52%	0.51	1.23	-0.84
13	2.47	-0.09	56.82%	0.44	1.27	-0.36

Looking at all component ratios at period t compared PD ratings at period t+1, results are closely related to those represented for the PD ratings at period t as expected.

Table 5.4.3: Average Ratios at Period t for Each PD Rating at Period t+3

PD_{t+3} Rating	Current Ratio (Inverse)	Working Capital to Gross Profit	Debt to Asset	Gross Profit to Total Liabilities	Funded Debt to EBITDA	Debt Coverage (Inverse)
4	0.31	0.97	15.65%	3.12	1.54	0.09
5	0.40	0.67	20.46%	2.63	1.91	0.26
6	0.68	0.57	27.49%	1.44	2.55	0.34
7	0.62	0.61	31.68%	1.46	4.15	0.68
8	0.69	0.54	35.52%	0.89	5.04	0.32
9	1.31	0.21	43.47%	0.73	4.47	0.55
10	0.98	0.96	35.41%	0.75	3.66	0.97
11	1.47	0.22	34.61%	1.03	5.82	0.26
12	0.84	0.59	41.83%	0.53	14.04	-0.57
13	0.59	0.90	39.75%	0.39	18.98	0.59

Tables 5.4.3 and 5.4.4 demonstrate that, as the timespan increases between the ratios for period t and the future PD rating at periods t+3 and t+5, the expectations in ratios per rating becomes less consistent. The definition of probability of default is the likelihood that a loan will go into default within the next 12 month time horizon. Therefore the PD rating is expected to be most effective within the same time parameters.

Volatility in weather, commodity prices, and input prices are only few of many variables that make it difficult to predict financial performance and/or ratios beyond one year. This illustrates the failure of ratios to predict a long time period and the need for updated ratios.

Table 5.4.4: Average Ratios at Period t for Each PD Rating at Period t+5

PD_{t+5} Rating	Current Ratio (Inverse)	Working Capital to Gross Profit	Debt to Asset	Gross Profit to Total Liabilities	Funded Debt to EBITDA	Debt Coverage (Inverse)
4	0.32	0.62	16.90%	3.31	1.12	0.41
5	0.67	0.64	22.68%	2.32	2.45	0.44
6	0.70	0.55	29.57%	1.32	3.82	0.81
7	0.69	0.66	33.42%	1.44	4.19	0.56
8	0.72	0.51	37.51%	0.86	3.82	0.40
9	1.29	0.23	42.31%	0.75	2.50	0.62
10	0.73	1.04	40.10%	0.84	5.32	1.12
11	1.06	0.11	36.48%	1.30	3.90	0.61
12	0.55	0.51	36.97%	1.10	4.78	0.54
13	0.30	2.26	32.40%	0.48	6.15	-0.25

The first set of OLS regression analyses determines how the current PD rating for an observation influences the PD rating for that observation one, three and five years into the future. A second set of regressions estimates how the ratios at period t influence the PD rating for that observation one, three and five years into the future. Finally, the last set of regressions estimate how the change in ratios from period t to periods t+1, t+3 and t+5 influence the change in PD ratings for the same.

For models using the independent variables involving PD_{t+1}, the number of observations are 8,420 compared to the total observations of 17,943. For models using the independent variables involving PD_{t+3}, the number of observations are 4,998 and for PD_{t+5}, the number of observations are 1,929.

Tables 5.5.1-5.5.3 represent the comparison of current year PD rating and ratios to the PD rating one year into the future (t+1). Table 5.5.1 shows regression results that reject the null hypothesis, suggesting that the current PD rating has a positive influence on the PD rating one year into the future. The equation for the regression is: $PD_{t+1} = 0.81\ PD + 1.147$. Thus, for every one unit positive change in current year PD rating, there is a 0.81 unit positive change in next year's PD rating. The current year PD rating is statistically significant at the 95% level in determining the PD rating one year into the future.

Table 5.5.1: Regression of PD_{t+1} and PD_t

Variable	Coefficients	Standard Error	t Stat	P-value
Intercept	1.147	0.049	23.633	0.000
PD_t	0.810	0.007	112.504	0.000

Goodness of Fit		ANOVA	
R Square	0.601	F	12657.174
Adjusted R Square	0.600	Significance F	0.000

The regression in Table 5.5.2 estimates their influence on PD rating one year into the future. Although the adjusted R^2 is lower than the PD rating to PD rating regression, this component ratio-based regression model represents the component contribution to future PD rating estimation. The details of each variable are discussed in depth in the ensuing paragraphs. In general, all independent variables are statistically significant and all signs, except for the FD/ EBITDA variable, are as expected. The regression equation is: $PD_{t+1} = 0.071\ CR(i) – 0.026\ WC/GP + 44.488 D/A - 0.011\ GP/TL + 0.008\ FD/EBITDA – 0.012\ DCR(i) + 5.138$

Table 5.5.2: Regression of PD_{t+1} and All Ratios at Period t

Variable	Coefficients	Standard Error	t Stat	P-value
Intercept	5.138	0.035	145.815	0.000
CR(i)	0.071	0.008	8.346	0.000
WC/GP	-0.026	0.009	-2.778	0.005
D/A	4.488	0.101	44.564	0.000
GP/TL	-0.011	0.003	-4.058	0.000
FD/EBITDA	0.008	0.001	5.397	0.000
DCR(i)	0.012	0.006	2.081	0.037

Goodness of Fit		ANOVA	
R Square	0.240	F	442.151
Adjusted R Square	0.239	Significance F	0.000

The results reject the null hypothesis for the inverted CR, suggesting that a one unit positive change in the ratio produces a 0.071 increase in the PD rating one year into the future. Thus, as the current ratio improves, the PD rating gets lower, indicating better overall financial health. Like the inverted CR, the regression results also reject the null hypothesis for WC/GP demonstrating statistical significance at the 95% confidence level. As the ratio of WC/GP increases by one unit, the future PD rating decreases by 0.026.

The null hypothesis for D/A ratio is also rejected. The regression rejects the null hypothesis for GP/TL and the sign on the coefficient is as expected. The regression also rejects the null hypothesis for FD/ EBITDA, the sign on the coefficient is correct and it is statistically significant at the 95% confidence level.

For the inverted DCR, the analysis rejects the null hypothesis and shows statistical significance at the 95% confidence level in suggesting that a one unit increase in the inverted DCR increases the future PD rating of a customer by 0.012 units. In other words, as the debt coverage ratio improves, the PD rating gets lower indicating decreased risk.

Both the CR and WC/GP variables are measures of liquidity. Similarly, both GP/TL and FD/ EBITDA are measures of earnings compared to liabilities. As a result, there is potential for multi-collinearity between these two sets of ratios. To compare these and all other ratios used in the regression, simple correlation was calculated for the regression in table 5.5.2 and is represented in the following table.

Table 5.5.2.1: Correlation of Regression Independent Variables

	CR(i)	*WC/GP*	*D/A*	*GP/TL*	*FD/EBITDA*	*DCR(i)*
CR(i)	1					
WC/GP	-17%	1				
D/A	14%	-15%	1			
GP/TL	-5%	-1%	-23%	1		
FD/EBITDA	0%	0%	11%	-6%	1	
DCR(i)	-4%	5%	4%	-3%	10%	1

With relatively small correlations percentages for all ratios, multi-collinearity does not appear to be present in the regression.

A third regression comparing the change in PD rating to the change in component ratios was estimated (Table 5.5.3) yielding the following equation: $PD_{t+1} = 0.020\ CR(i) – 0.013\ WC/GP + 2.896\ D/A – 0.001\ GP/TL + 0.003\ FD/EBITDA - 0.005\ DCR(i) – 0.082$.

Table 5.5.3: Regression of the Change in PD Rating and Ratios from Period t to Period t+1

Variable	Coefficients	Standard Error	t Stat	P-value
Intercept	-0.082	0.011	-7.123	0.000
CR(i)	0.020	0.006	3.227	0.001
WC/GP	-0.013	0.007	-1.955	0.051
D/A	2.896	0.142	20.339	0.000
GP/TL	-0.001	0.002	-0.609	0.543
FD/EBITDA	0.003	0.001	3.455	0.001
DCR(i)	-0.005	0.003	0.082	-0.011

Goodness of Fit		ANOVA	
R Square	0.056	F	82.511
Adjusted R Square	0.055	Significance F	0.000

The adjusted R^2 reduces for this model compared to those previously discussed. With the exception of the inverted DCR, all signs are as expected. Statistical significance of variables is generally consistent to the previous model with the following differences. GP/TL is not statistically significant but the sign is as expected. The inverted DCR is statistically significant but the sign is not as expected. It may be that inaccuracies in the data used for the inverted DCR are having an impact in rendering the unexpected sign when table 5.5.1 shows that the sign is correct.

Correlation calculations were also run for the model represented in table 5.5.3 with similar results indicating that the highest correlation is between D/A and GP/TL at 15% correlation and all others less correlated than that.

The 5.6 and 5.7 series of tables imitates the set above, using PD_{t+3} and PD_{t+5} variables rather than PD_{t+1}. As previously mentioned above, a review of the analysis shows that the goodness of fit, expected signs and statistical significance all decline in effectiveness as the timespan from ratio to future PD rating increases.

Table 5.6.1: Regression of PD_{t+3} and PD_t

Variable	Coefficients	Standard Error	t Stat	P-value
Intercept	2.137	0.089	24.114	0.000
PD_t	0.649	0.013	48.708	0.000

Goodness of Fit		ANOVA	
R Square	0.322	F	2372.455
Adjusted R Square	0.322	Significance F	0.000

Consistent with the t+1 results above, table 5.6.1 shows that the current PD rating coefficient has the expected sign and the variable is statistically significant at the 95% confidence level. The goodness of fit is lower than the similar t+1 regression but the regression suggests that current PD rating is a significant predictor of the PD rating three years into the future.

Table 5.6.2: Regression of PD_{t+3} and All Ratios at Period t

Variable	Coefficients	Standard Error	t Stat	P-value
Intercept	5.081	0.050	102.285	0.000
CR(i)	0.050	0.012	4.057	0.000
WC/GP	0.004	0.014	0.290	0.772
D/A	4.398	0.147	29.929	0.000
GP/TL	-0.009	0.005	-2.002	0.045
FD/EBITDA	0.011	0.002	5.534	0.000
DCR(i)	0.017	0.009	2.045	0.041

Goodness of Fit		ANOVA	
R Square	0.196	F	202.337
Adjusted R Square	0.195	Significance F	0.000

Table 5.6.2 shows the regression results from comparing current year ratios to the dependent variable of the PD rating three years into the future (t+3). The goodness of fit is less than the similar regression for t+1 represented in table 5.5.2 which is expected. The signs on coefficients remained as expected for the variables CR(i), D/A, GP/TL, FD/EBITDA and DCR(i). The aforementioned ratios are also statistically significant at

the 95% confidence level. WC/GP both shows the opposite sign than expected and is not statistically significant.

Table 5.6.3: Regression of the Change in PD Rating and Ratios from Period t to Period t+3

Variable	Coefficients	Standard Error	t Stat	P-value
Intercept	-0.074	0.020	-3.653	0.000
CR(i)	0.027	0.007	3.886	0.000
WC/GP	-0.038	0.011	-3.380	0.001
D/A	4.349	0.183	23.739	0.000
GP/TL	-0.002	0.003	-0.688	0.492
FD/EBITDA	0.002	0.001	1.480	0.139
DCR(i)	-0.012	0.006	-1.941	-0.023

Goodness of Fit		ANOVA	
R Square	0.121	F	114.285
Adjusted R Square	0.120	Significance F	0.000

The regression results from the change in PD and change in ratios from period t to period t+3 are represented in table 5.6.3. The goodness of fit is higher in this change regression than the change from period t to period t+1, suggesting that the greater change in ratios inherent with longer periods of time are more explanatory to the one unit PD rating changes set forth as the dependent variable in this regression. The independent variables are statistically significant at the 95% confidence level, except for GP/TL and FD/EBITDA. The coefficients on the variables have the expected signs with exception of DCR(i).

Table 5.7.1: Regression of PD_{t+5} and PD_t

Variable	Coefficients	Standard Error	t Stat	P-value
Intercept	2.590	0.160	16.161	0.000
PD_t	0.552	0.024	23.025	0.000

Goodness of Fit		ANOVA	
R Square	0.216	F	530.146
Adjusted R Square	0.215	Significance F	0.000

Consistent with the t+1 and t+3 results, table 5.7.1 shows that the current PD rating coefficient has the expected sign and is statistically significant at the 95% confidence level. The goodness of fit is lower than the similar t+1 and t+3 regressions but the results suggest that current PD rating is significant related to PD rating five years into the future.

Table 5.7.2: Regression of PD_{t+5} and Ratios at Period t

Variable	Coefficients	Standard Error	t Stat	P-value
Intercept	5.052	0.079	63.648	0.000
CR(i)	-0.001	0.016	-0.031	0.975
WC/GP	0.007	0.021	0.319	0.750
D/A	4.067	0.233	17.475	0.000
GP/TL	-0.008	0.007	-1.087	0.277
FD/EBITDA	0.001	0.004	0.161	0.872
DCR(i)	-0.003	0.013	-0.242	0.809

Goodness of Fit		ANOVA	
R Square	0.155	F	58.660
Adjusted R Square	0.152	Significance F	0.000

Table 5.7.2 shows the regression results from comparing current year ratios to the dependent variable of the PD rating five years into the future (t+5). The goodness of fit is less than the similar regressions for t+1 and t+3 represented in tables 5.5.2 and 5.6.2 which is expected. The accuracy of signs on coefficients breaks down further in this model. Those that show signs as expected are the D/A, GP/TL and FD/EBITDA variables while all others show signs on coefficients that are not expected. The only variable that is statistically significant at the 95% confidence level in this model is D/A. All others are not significant in influencing the t+5 PD rating.

Table 5.7.3: Regression of the Change in PD Rating and Ratios from Period t to Period t+5

Variable	Coefficients	Standard Error	t Stat	P-value
Intercept	-0.199	0.035	-5.730	0.000
CR(i)	0.020	0.011	1.881	0.060
WC/GP	-0.027	0.017	-1.558	0.119
D/A	4.462	0.267	16.734	0.000
GP/TL	0.001	0.004	0.124	0.901
FD/EBITDA	0.009	0.003	3.668	0.000
DCR(i)	0.009	0.010	0.928	0.353

Goodness of Fit		ANOVA	
R Square	0.152	F	57.453
Adjusted R Square	0.149	Significance F	0.000

The regression results from the change in PD and change in ratios from period t to period t+5 are represented in table 5.7.3. The goodness of fit improves slightly from the similar regression for t+3 in table 5.6.3, providing additional evidence of greater explanatory power for changes in PD rating (dependent variable) when a longer period of time creates greater variation in ratios (independent variables). The coefficients have the expected signs with the exception of GP/TL. Statistically significant variables at the 95% confidence level are CR(i), D/A and FD/EBITDA. WC/GP, GP/TL and DCR(i) are not statistically significant in this model.

CHAPTER VI: CONCLUSION

Empirical customer account data from 2006-2012 was examined to review the probability of default (PD) rating methodology for production agricultural accounts used within the risk rating system implemented by a FCS association. The data showed that average PD ratings held relatively consistent over the years with any fluctuation driven largely by commodity price cycles and how they affect the overall financial position of farming and ranching operations. Furthermore, although the average PD-rating of accounts stayed within the desired risk parameters of the association, distribution of the majority of PD ratings shifted to higher quality by two rating categories in the last year compared to the first.

Regression analysis was completed with the objective of increasing understanding of the accuracy of the methodology used by the association in predicting the migration of accounts across its currently-established PD rating categories. Various ratios were considered in the analysis, some of which are currently used by the association and others that are alternatives.

The results suggest that current ratio appears to be superior to working capital to gross profit as a liquidity measure in predicting PD rating migration. Funded debt to EBITDA is potentially more effective in predicting PD rating movement as a measure of earnings to debt than gross profit to total liabilities, although it could be deduced that neither ratio is pertinent to the model. The change of these ratios over time appear to be weaker indicators of the change in PD rating potentially due to the variable nature of annual earnings of production agriculture operations due to commodity price volatility. The debt coverage ratio is important as it relates to future PD migration, though the same variability in commodity price volatility suggests the need implement multi-year averaging for calculation of earnings-based ratios. All ratios in the analysis are important in predicting the PD rating of observations one year into the future for production agriculture operations. To further test the predictive ability of the PD ratings, similar regression analyses were completed comparing current year rating and ratios to future PD ratings beyond one year, specifically for three and five years. Results from these additional regression models indicate that current year PD rating and ratios are less effective in predicting future PD ratings beyond one year.

Furthermore, because of the variation in regression results that this analysis demonstrates between one, three and five years into the future, it is important to regularly capture ratio and rating information to adequately assess loan portfolio credit quality. Capturing this data at least annually is recommended.

Some recommendations exist for improving the objectives set forth in this analysis. The data came from the association's financial analysis software which contains a variety of financial sets that are at various stages of completion. This increases the risk that some of the financial information used was not complete because the processes for loan origination do not demand that everything entered into the analysis software be ready to run through the PD model, which resides within the disparate loan origination and accounting software that receives an import of completed financial information from the financial analysis program. As the association continues to improve the integration of these two functions, more accurate information will be available to enhance this analysis.

In the actual PD model used by the association for production agriculture operations, the debt coverage ratio is calculated by dividing a three year average of earnings available for debt service by projected debt payments. The state of the raw data used in this analysis made it difficult to recreate the averaging so the actual earnings for one year were used along with the actual debt service for that year. This created greater volatility in this measure, which may negatively impact results for this ratio. The same is true for the gross profit to total liabilities ratio. Calculating these ratios more exactly to how they are used in the model would improve this analysis.

Finally, the PD ratings assigned to each observation are based on the weighted average of all components used in the PD model. The weightings for each component are decided upon by credit underwriting leadership based on how strongly it is decided that the particular PD component is to influence the overall calculated PD rating. This could affect how the current rating ties into the components to influence the future rating. Adjusting to normalize the influence of weightings may also improve the analysis.

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